APPENDIX A

BACKGROUND ARTICLE ON THE PRIDEM AND PRIDEL MODELS

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Theory and Methodology

Modeling competitive pricing and market share: Anatomy of a decision support system *

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Abstract: Even with today's high emphasis on management decision support systems, relatively little has been published on the motivations, tribulations, and post mortems that generally accompany the development of such systems. This paper reports (in a mixture of narrative style and more formal model exposition) how a computerized decision support system for optimal price determination was developed, implemented, and finally applied to a broad range of industry problems.

Keywords: Pricing; demand analysis; conjoint analysis; multiattribute preference

1. Introduction

Product and service pricing is one of the oldest (and still very important) tools of the marketing executive. Each day business firms face questions like the following:

1. Competitor X has just increased its price by five percent. Should we match it, or stand pat?
2. How should we price our new product, which offers several technical advantages over current offerings?
3. How should we set prices among competing items in our current product line?

Answers to these questions are hard to find for at least two reasons. First, given a set of existing prices and market shares for products in a competing product class, it is often difficult to predict new shares accurately if one or more prices were to change. Second, it is difficult to predict how competitors will react to others' price changes.

Marketing researchers have dealt with the first question by proposing several new marketing research methods that show promise for augmenting information obtained from older approaches. Historically, the measurement of price-demand relationships has relied on statistical methods applied to either cross-sectional or time series data (e.g., Wittink, 1977). However, newer approaches, such as those based on laboratory studies (Pessemier, 1960), instore experiments (Doyle and Gidengil, 1977), test market simulation (Silk and Urban, 1978), and willingness-to-pay surveys (Monroe and Della Bitta, 1978) have received increased attention and, in some cases, commercial application.

Even more recently, conjoint-based methods (Mahajan, Green, and Goldberg, 1982; Louviere and Woodworth, 1983; Wyner, Benedetti, and Trapp, 1984) have considered explicitly designed competitive product profile descriptions. Respon-

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dents either pick their preferred choice from the set of alternatives, indicate their likelihood of choosing each option, or state their preferences for alternative allocations of a common resource across products or activities competing for that resource (Carroll, Green, and DeSarbo, 1979).

A prototypical procedure entailing tradeoff techniques is that proposed by Mahajan, Green, and Goldberg (MGG). Their survey data collection approach is a modification of one originally proposed by Jones (1975). Respondents are shown profile descriptions of P products, each with an associated brand name and price. Profiles are designed according to fractional factorials in which attributes and levels are idiosyncratic to each brand. Respondents allocate a constant sum (typically 100 points) across each stimulus option indicating the likelihood that they would choose each option, given the stated prices for each alternative. MGG employ a conditional logit model (Theil, 1969) to estimate parameter values that satisfy the following sum and range constraints:

1. The estimated probability of choosing some p-th brand ranges between zero and one.
2. The sum of the choice probabilities across all P brands (including an all-other-brands category, if appropriate) equals unity.

While MGG discuss how their approach might be used in actual business situations, they also add that their experience with applying the model to real-world problems is quite limited.

1.1. Inputs from the business world

As we mulled over the idea of adapting some of the conjoint methodology to the measurement and strategy issues related to optimal pricing, we sought the advice of several commercial marketing research firms. Gradually, a pattern emerged regarding their views about what managers would like to see in a price/demand model:

1. The approach should be able to utilize survey methods, similar to the kinds of buyer tradeoff data that are collected in applied conjoint studies.
2. The model should be able to consider not only the impact of price changes on market share but also the effect on share of non-price attribute changes on the part of any or all competitors.
3. The model should be able to make market share predictions at both the total market and individual market segment levels.
4. The model should be capable of examining interactions among different competitors' prices and non-price attribute levels.
5. The model should be 'decomposable' in the sense of allowing the client to focus attention on the behavior of a single product's share as a function of individual competitors' prices and non-price activities.
6. The model should be capable of being calibrated to actual starting (i.e., existing) market shares and prices.
7. The model should contain an 'optimizing' feature in which the user can find the best price for a given product, conditional on fixed prices for competitors and specified levels of all non-price attributes, self and competitors.
8. The model should be flexible enough to allow interpolation across discrete price points.
9. The model should be user friendly and, if possible, adaptable to a personal computer.

With these desiderata in mind, we set about the task of constructing a suitable data collection method, parameter estimation technique, and price optimizing routine.

1.2. Borrowing from the past

Fortunately, earlier work in componential segmentation (Green, Krieger, and Zelnio, 1989) led to the development of a conjoint model for forecasting buyers' likelihoods of purchase from information about product attribute preferences and buyer backgrounds (e.g., demographics, life styles, current brand usage, etc.). The PROSIT (PROduct SITuation) model contained a number of relevant features for the current effort, namely PROSIT's ability to estimate parameter values for both product attributes and buyer attributes, as well as selected two-way, within-set and between-set interactions.

Furthermore, PROSIT contained an optimizing feature wherein one could find the best product profile for a given market segment or the best segment for a given product.

In the PROSIT model, all parameters are estimated as though each predictive variable is categorical (i.e., predictors are treated as dummy variables in the spirit of conjoint analysis). The response variable is 'univariate' – typically, a buyer's subjective likelihood of choosing a specific brand or service supplier as a joint function of product profiles (for that brand and competitive brands) and respondent background variables.

In contrast, our present problem emphasized an underlying continuous variable (i.e., price) and entailed a 'multivariate' response, namely, the respondent's subjective likelihood of choosing each of P products as a function of their product attributes, their prices, and the buyer's background attributes. Still, the earlier PROSIT model seemed like a good place to start. On the plus side, it had been successfully applied in a variety of industrial applications (particularly in the pharmaceutical and computer industries) and had already been adapted for interactive, personal computer applications.

2. Decisions, decisions

At this point we had a starting point for the PRIce-DEMand model (PRIDEM). However, a number of decisions still had to be made on adapting the PROSIT model for pricing and, in particular, incorporating a multivariate response variable. PROSIT was estimated by OLS dummy variable regression. Its optimizer employed a heuristic for finding optimal combinations of product and/or segment attribute levels from the full Cartesian product set of attribute levels. In contrast, our current interest centered on price optimization, conditional on given settings of all other attributes.

2.1. *Handling the price attribute*

In keeping with conjoint methodology, it seemed appropriate to maintain the treatment of all attributes (including price) as categorical, encoded as dummy variables. From a pragmatic viewpoint this would allow us to use a portion of the same software already in place for fitting the PROSIT model. Second, we could avail ourselves of highly efficient, fractional factorial designs for setting up the product and price stimulus design that would estimate all main effects as well as selected two-way interactions. Moreover, these (orthogonal) designs are flexible enough to accommodate enough price levels (e.g., five to nine per brand) to approximate a continuous part-worth function rather closely.

Why not just select a polynomial (e.g., quadratic) to represent part worths for the price variable? One of the problems with this approach is that the resulting curve is sensitive to error. In fact, it is possible that the fitted curve could depart rather markedly from the actual responses associated with the experimentally designed price points. Clearly, with polynomial fitting there is no requirement that the curve 'go through' the response value observed at each discrete experimental price point.

In contrast, by using *splines* we could make sure that the response function passed through the knots (i.e., price points). Furthermore, we could make the function smooth between each pair of knots so that simple (classical) methods of optimization could be used to find the solution that maximized the sponsor's contribution to overhead and profit (conditional on fixed prices for competitive products).

Accordingly, we set up a computer routine for fitting one and two-dimensional splines where the knots represented the discrete price levels used in the original experimental design underlying the competitive product profiles. The Appendix describes this procedure.

2.2. *Making the model multivariate*

A second problem with the adaptation of PROSIT to PRIDEM was how to deal with the multivariate response variable. The PROSIT model is fit by ANOVA-like, OLS regression. If the original PROSIT response variable were quantal (e.g., 1 or 0) or if the response were each respondent's subjective likelihood of purchase on a 0 to 1.0 scale, no attempt was made in PROSIT to transform it to a logit (as was done in Mahajan, Green, and Goldberg, 1982).

Why not, then, set up a multinomial logit model with brand and product interactions, rather than fitting individual linear probability models and *then* finding market shares on a post hoc basis? We chose to maintain OLS fitting and the linear probability model for two reasons. First, the PROSIT model has a rather elaborate, built-in cross validation feature which we wished to retain for assessing the predictive accuracy of prices.

market segments, and non-price attributes on a single product's likelihood of purchase. This could be applied to each product, in turn, as a way to see if some part worth functions are poorly estimated.

Second, despite the theoretical attractiveness of the multinomial logit (see Mahajan, Green, and Goldberg, 1982), we noted that Brodie and De Kluyver (1984) have reported that linear probability models, with post hoc adjustment (to respect non-negativity and sum constraints), have fared as well as the more complex multinomial logit models in terms of empirical market share validation. (Still, it should be mentioned that the current structure of PRIDEM could be reformulated in terms of a multinomial logit.)

With these preliminary decisions made, it was then time to formulate the model.

3. The PRIDEM model

To motivate our description of the PRIDEM model, consider a situation in which a pharmaceutical firm wishes to increase the price of its antihypertensive drug, brand A. There are five other competing brands in the market niche of interest to brand A's producers: B, C, D, E, and F. The producers of brand A are able to estimate per-unit variable production/distribution costs for each of the six competitive brands.

In designing the marketing research survey, brand A's producers considered four price levels each for brands A, B and C, three levels each for D and E, and two levels for the more remote competitor, brand F. In addition, they selected one three-level non-price attribute describing brand A's dosage schedule: once daily, twice daily, or three times daily.

A conjoint orthogonal design of 64 profile descriptions was set up. Each respondent received eight of the profile descriptions, drawn from the master design. For each description the respondent was asked to allocate 100 points across the six competitive brands so as to reflect the proportion of hypertensive patients for whom each drug would be prescribed, under the stated conditions. (Prior to this task each respondent similarly evaluated a base-case profile showing the current prices of each brand and brand A's current dosage level of three times daily.) Figure 1 shows an

CARD D25 I.D.# ________

Share of patients		Current price per day's therapy	+5%	+10%	+15%
	Brand A dosage twice/day	$1.97			
	Brand B	$1.88			
	Brand C				$2.12
	Brand D		$2.29		
	Brand E		$2.09		
	Brand F				$2.09
Total 100%					

Figure 1. Illustrative stimulus card

illustrative stimulus card for one of the experimental conditions.

Respondents were classified, a priori, by five segment attributes: specialty (cardiologists versus general practitioners); age (under 35, 35 and older); type of practice (solo versus group); current brand favorite (brand A versus others); and patient load, within specialty (above median versus below median). [1]

3.1. Preliminaries

In describing the PRIDEM model more formally, we first consider the question of estimating the market shares for each brand, as a function of manipulated product/price variables and respondent characteristics. Market shares are assumed to depend on three types of attributes: (a) market segment attributes; (b) non-price (e.g., product) attributes; and (c) price attributes. We let

$l_1, l_2, \ldots, l_S$

denote the number of levels associated with each of the S segment attributes. In the illustrative problem these attributes describe the decision makers, such as specialty (cardiologist, general practitioner), age (age under 35, 35 and over), and so on.

Similarly, we let

$m_1, m_2, \ldots, m_T$

denote the number of levels associated with each of the T non-price attributes. In the illustrative problem there is only one non-price attribute: dosage (once daily, twice daily, three times daily).

Finally, the market shares are also assumed to depend on the brands' prices. We assume $R \leq P$ price attributes; this allows for the case in which a subset of size $P - R$ of the P brands does not vary with respect to price. We let

$n_1, n_2, \ldots, n_R$

denote the number of levels of each of the R price attributes. To simplify notation, we further assume that the brands are ordered, so that brand i refers to the brand whose price is varying in price attribute i. Associated with each level of each price attribute is an actual price (e.g., in dollars per day's therapy). Prices are denoted by:

$\Pi_{rj} \quad r = 1, 2, \ldots, R; \; j = 1, 2, \ldots, n_r.$

We shall use i, j, and k to subscript attribute levels in general.

3.2. Segment components

The segment attributes are used to define the universe over which the market shares are computed. We specify a segment by assigning selected attribute levels to the S segment attributes. We can combine segments by aggregation. More generally, we can construct any universe of interest by a set of non-negative segment weights,

$w_{sj}, \quad s = 1, 2, \ldots, S; \; j = 1, 2, \ldots, l_s,$

so that

$$\sum_{j=1}^{l_s} w_{sj} = 1 \quad \text{for } s = 1, 2, \ldots, S.$$

In particular, a given segment with levels $\{i_1, i_2, \ldots, i_S\}$ is captured by setting

$w_{j i_j} = 1 \quad \text{for } j = 1, 2, \ldots, S$

and

$w_{jk} = 0; \quad \text{otherwise}.$

Through the use of weighting coefficients PRIDEM can select a specific weighted universe across all attributes with (say) weights of 0.7 and 0.3 for cardiologist and GP, respectively, and weights of 0.2 and 0.8 for under 35 years and 35 years or older, respectively. Given the five two-level background descriptors, described above, we have a maximum of 32 distinct segments.

Later on, we shall describe how the 'optimal' price for each product is determined, given stated prices for all other brands. The optimal price will be defined by the value that maximizes contribution to overhead and profit, defined by the expression:

Industry sales units · (price − variable cost/unit of brand p) · (market share of brand p).

(In applying the computer-based PRIDEM model, industry sales are usually set, for convenience, at 1.0.)

[1] It should be noted that the approach does not require segment atributes to be dichotomous; however, the model implemented here assumes that all attributes are discrete.

3.3. Market share model

Associated with each brand p is an estimated market share

$$f^{(p)}(\boldsymbol{k};\, j,\, \boldsymbol{w})$$

where $\boldsymbol{k}$ is a vector (of length R) of prices. j is a vector (of length T) of levels for the non-price attributes, and w is S vectors (of respective lengths $l_1, l_2, \ldots, l_S$) denoting the universe of decision makers (i.e., the physicians).

The function $f^{(p)}$ is obtained by first fitting a main effects model to the raw response data (i.e., the likelihood of prescribing the p-th brand in question) where the predictors are the S segment attributes, the T non-price attributes, and the R price attributes, all expressed as dummy variables. Selected two-way interactions are then added to the model in a sequential, stagewise manner (Green and DeSarbo, 1979). As noted above, interactions can be either within segment, non-price, or price attributes, or between segment, non-price, or price attributes.

The fitting of main effects and interactions yields a set of regression-based functions $h^{(p)}$, $p = 1, 2, \ldots, P$, one for each product, as a preliminary step toward obtaining $f^{(p)}$. We first discuss how each $h^{(p)}$ is obtained and then how it is adjusted to find $f^{(p)}$. The model is described, in part, by its L interactions. As noted earlier, interaction l^* can be of several differing types:

$(q_{l_1^*}, q_{l_2^*})$ with $q_{l_2^*} \geq q_{l_1^*}$.

We have the combinations as shown in Table 1.

Attribute levels with associated interaction l^* are denoted by $(u_{l_1^*}, u_{l_2^*})$. For example, if $q_{11} = 2$, $q_{12} = 3$, $u_{11} = 3$, and $u_{12} = 4$, then the first interaction is between the third non-price attribute and the fourth price attribute.

Describing the formal regression model for estimating each individual product's $h^{(p)}$ is a bit messy because of the large variety of possible interaction terms. We define $h^{(p)}$ as

$$h^{(p)}(i, j, k) = A^{(p)} + \sum_{s=1}^{S} B^{(p)}_{s, i_s} + \sum_{t=1}^{T} C^{(p)}_{t, j_t} + \sum_{r=1}^{R} D^{(p)}_{r, k_r} + \sum_{l^*=1}^{L} E^{(p)}_{l^*}(i, j, k;\, q_{l_1^*}, q_{l_2^*}, u_{l_1^*}, u_{l_2^*}) \quad (1)$$

where

$A^{(p)}$ denotes the intercept term for product p's function,

$B^{(p)}_{s, i_s}$ denotes the main effect partworth for level i_s of segment attribute s,

$C^{(p)}_{t, j_t}$ denotes the main effect partworth for level j_t of non-price attribute t,

$D^{(p)}_{r, k_r}$ denotes the main effect partworth for level k_r of price attribute r, and

$E^{(p)}_{l^*}(i, j, k;\, q_{l_1^*}, q_{l_2^*}, u_{l_1^*}, u_{l_2^*})$ is an entry in the matrix associated with interaction l^*. The specific entry depends on i, j, k, $q^*_{l_1}$, $q_{l_2^*}$, $u_{l_1^*}$ and $u_{l_2^*}$

Table 1

$q_{l_1^*}$	$q_{l_2^*}$	Nature of interaction
1	1	Segment by segment attribute
1	2	Segment by non-price attribute
1	3	Segment by price attribute
2	2	Non-price by non-price attribute
2	3	Non-price by price attribute
3	3	Price by price attribute

3.4. Base-case calibration

To calibrate each individual brand model, we adjust each $h^{(p)}$ obtained from the individual product regressions to a base-case profile. This is accomplished by finding $h^{(p)}$ for this profile and then multiplying all the parameters (A, B, C, D, E) by $b^{(p)}/h^{(p)}$ where $b^{(p)}$ is the given market share for the base-case profile.

Finally, we obtain the market share function $f^{(p)}$ from $h^{(p)}$ by normalizing the individual $h^{(p)}$ values by means of the function

$$f^{(p)}(\boldsymbol{k};\, j,\, \boldsymbol{w}) = \frac{\sum_i w_i \left(h^{(p)}(i, j, \boldsymbol{k})\right)^+}{\sum_{q=1}^{P} \left[\sum_i w_i \left(h^{(q)}(i, j, \boldsymbol{k})\right)^+ \right]} \quad (2)$$

where $(x)^+ = \max(x, 0)$, $w_i = \Pi_{s=1}^{S} w_{s, i_s}$ and h has been previously adjusted to base-case market shares, as described above. Note that if $h^{(p)}(i, j, k) = 0$ for all p, then $f^{(p)}(k, j, w) \equiv 1/P$.

3.5. Additional remarks

As noted earlier, we fit each $h^{(p)}$ regression function as a simple linear probability model in which predicted values need not obey a 0–1 range constraint; simple OLS regression is employed. Similarly, $f^{(p)}$ is obtained by a normalizing procedure which simply insures that all of the individual $h^{(p)}$ predicted values are non-negative. (As described earlier, other procedures, including multinomial logit, could be used.)

It should also be pointed out that the sequential fitting of two-way interactions requires that attention be paid to the significance testing of additional terms. This is implemented by procedures described in Green and DeSarbo (1979). In addition, each individual $h^{(p)}$ model is cross-validated at each stage in the interaction fitting procedure. Cross-validated predictions are employed as the principal guide to the selection of appropriate interaction terms, once the main effects have been fitted.

4. Price interpolation and optimization

There are two remaining aspects of the model that are not explained fully by (1) for $h^{(p)}$. (Since the discussion below applies to all p, we now omit the superscript.) We first note from the preceding discussion that market shares can only be predicted at the price levels Π_{rj} associated with the price attributes. It is desirable to be able to interpolate, i.e., to predict market shares at prices Π_r, $r = 1, \ldots, R$, that are not limited to the original Π_{rj}. Second, we have not discussed how to find the optimal prices Π_r^*, $r = 1, \ldots, R$.

4.1. Interpolation procedure

The solutions to both of these problems depend upon the method of interpolation between successive price levels Π_{rj} and Π_{rj+1}. To this end, we assume that the weightings over segments and levels for non-price attributes are fixed, in any given run of the model. The function, h, can then be written as $h(\Pi_1, \ldots, \Pi_R)$ where $\Pi_1, \ldots, \Pi_R$ denotes prices for the R price attributes. Since we fit an additive model with interactions, we can write,

$$h(\Pi_1, \ldots, \Pi_R) = A + \sum_{r=1}^{R} g_r(\Pi_r) + \sum_{r \neq s} g_{rs}(\Pi_r, \Pi_s) \tag{3}$$

where A includes the intercept, and the main effects for segments and nonprice attributes and interactions that do *not* involve price attributes; g_r includes the main effect for price attribute r and all interactions involving the r-th price attribute with a segment attribute or a non-price attribute; g_{rs} refers to the interaction between the r-th and s-th price attributes (where $g_{rs} \equiv 0$ if this interaction does not appear in the model).

The function h is R-dimensional with known values on a lattice of points Π_{rj}, $r = 1, \ldots, R$, $j = 1, \ldots, n_r$. We could fit a spline (Greville, 1969; Rice, 1969) to h, treating the Π_{rj} as the knots; however, we would not be using all of the known information. Since g_r and g_{rs} are known at Π_{ri} and (Π_{rj}, Π_{sk}) we can fit one and two-dimensional splines respectively to these functions, thus determining h. The Appendix describes how this is done.

4.2. Finding the optimal value for price

From discussion in the previous sections (and the Appendix), we only need to consider Π_r between two knots. Hence,

$$h^{(p)}(\Pi_r) = \sum_{i=0}^{K} \beta_{pi} \Pi_r^i \quad \text{for } \Pi_{rj} \le \Pi_r \le \Pi_{rj+1} \tag{4}$$

where β_{pi} includes the assumed specified values for the prices of the remaining $p-1$ products. Hence, the market share for product p is

$$M_p = \frac{\sum_{i=0}^{K} \beta_{pi} \Pi_r^i}{\sum_{j=1}^{P} \sum_{i=0}^{K} \beta_{ji} \Pi_r^i} \tag{5}$$

and the objective function, $M_p(\Pi_r - C_r)$, can be written as:

$$Z(\Pi_r) = \frac{\gamma_0 + \gamma_1 \Pi_r + \cdots + \gamma_K \Pi_r^K}{\delta_0 + \delta_1 \Pi_r + \cdots + \delta_K \Pi_r^K} (\Pi_r - C_r). \tag{6}$$

It is straightforward to solve (6) when $Z'(\Pi_r) = 0$, which is an equation of order $2K$, and compare these results to the values at the knots.

In particular, if $K = 1$, then

$$Z(\Pi_r) = \frac{(\gamma_0 + \gamma_1 \Pi_r)(\Pi_r - C_r)}{\delta_0 + \delta_1 \Pi_r}.$$

Hence,

$$Z'(\Pi_r)$$

$$= \frac{(\delta_0 - \delta_1 \Pi_r)(\gamma_0 - 2\gamma_1 \Pi_r - C_r\gamma_1) - (\gamma_0 - \gamma_1 \Pi_r)(\Pi_r - C_r)\delta_1}{(\delta_0 - \delta_1 \Pi_r)^2}$$

$$= 0$$

$$\Rightarrow \Pi_r = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a}$$

where

$$a = \gamma_1\delta_1, \quad b = 2\gamma_1\delta_0,$$

$$c = (\gamma_0 - C_r\gamma_1)\delta_0 + C_r\gamma_0\delta_1.$$

We find the two points such that $Z'(\Pi_r) = 0$ for $\Pi_{rj} \le \Pi_r \le \Pi_{rj+1}$ for $j = 0, 1, \ldots, n-1$. Finally, we compare Z at these two points, provided that the points are in the appropriate (Π_{rj}, Π_{rj+1}) to determine Π_r^*.

5. A real-world application

The PRIDEM model and decision support system have been implemented on both the main frame (Vax 8700) and the personal computer. A number of industrial applications have been made of PRIDEM over the past three years. We illustrate PRIDEM's application with an actual industry example involving two pharmaceutical companies' pricing strategies in the marketing of a diet supplement for use by hospital patients who have trouble swallowing traditional foodstuffs. (All data have been disguised to respect sponsor confidentiality.)

5.1. Study background

For several years, only one pharmaceutical firm, hereafter called Alpha, had been marketing a special diet supplement for hospital patients with esophagus ailments. The product was designed for drinking (through a straw); it contained a balanced set of nutrients. More recently, a second firm, hereafter called Beta, had developed its own diet supplement. Several of its product properties differed from those of Alpha as well as its marketing and pricing plans.

Prior to Beta's entry, Alpha's ongoing price for its diet supplement was \$41 per day per patient. Beta believed that Alpha's short run monopoly could be upset by penetration pricing; accordingly, Beta introduced its product at only \$38 per individual per day. The results were dramatic; in two years, Beta had penetrated the market to such an extent that the two firms' shares were 28% and 72%, respectively, for Alpha and Beta. At this point, Beta wondered whether its price was 'right' (in the sense of optimizing its contribution to overhead and profit) and what the implications might be if Alpha were to change its still-current price of \$41.

5.2. Designing the conjoint survey

A conjoint study was designed to obtain data for use in the PRIDEM model. First, Beta personnel discussed possible non-price attributes that could affect market shares independently (or possibly interactively with price). Four such attributes were identified:

1. Packaging for Alpha: 4-ounce can (current) versus 6-ounce can (prospective); Beta's dosage was already at 6 ounces per can.
2. Extended contract price guarantee for Alpha: NO (current) versus YES (prospective); Beta had no price guarantee.
3. Concentration of amino acids for Beta: low concentration (current) versus high concentration (prospective); Alpha's concentration was already slightly lower than Beta's current concentration.
4. Educational aids for Beta: NO (current) versus YES (prospective); Alpha already had educational aids.

In addition to the non-price attributes, Beta's management considered several possibilities for identifying market segments. Management settled on two primary segmentation bases:

1. Type of respondent (i.e., as an influence on which brand is purchased)
   a. nurses,
   b. doctors,
   c. hospital pharmacists.
2. Size of hospital
   a. Large (over 500 beds),
   b. small (fewer than 500 beds).

Finally, Beta management estimated that variable costs for producing and distributing the diet supplement were about equal between the two firms; they estimated these costs at $19 per individual per day.

A sample of 390 respondents was selected, according to the two stratifying criteria (profession and hospital size). All interviews were conducted by personal administration, following pre-arranged appointments. Respondents received honoraria for their participation.

The conjoint portion of the interview was based on a master orthogonal experimental design of 50 profile cards. Each profile card contained information on brand names, non-price attribute levels under each brand name, and prices per patient day. The prices were drawn from the following sets:

1. Alpha – $43, $41 (current), $34, $28, $21.
2. Beta – $41, $38 (current), $34, $28, $21.

Each respondent first received a 'base case' profile card, followed by five cards (balanced with respect to prices) from the overall orthogonal design. For each card, the respondent was asked to indicate what his/her recommendation would be to purchasing agents responsible for choosing the diet supplement supplier. Each respondent was asked to split 100 points (constant sum scale) between the two potential suppliers, reflecting their likelihood of recommending each.

Other background information, including the hospital's current use of diet supplements, respondent's role in the contract decision process, years of experience, etc., were also collected for cross-tabulation with the conjoint results.

6. Running the PRIDEM program

Figure 2 shows a portion of the PRIDEM computer run for the problem described above. Illustratively, we input the base-case prices (as a control) and note, of course, the same market shares as originally read in (e.g., Alpha's share is 0.28). We also observe that the contribution to overhead and profit per patient day is $6.16 and $13.68 for Alpha and Beta, respectively.

6.1. Overall market analysis

We next consider alternative pricing strategies, conditioned on the non-price attributes remaining at their original (current) levels. Suppose we wish to find Alpha's optimal price at base-case levels. We enter instructions accordingly and find from Figure 2 that its optimal price is $36.19, a decrease from its current level of $41. If Alpha were to reduce its price, with no retaliation from Beta, its share would increase ten percentage-points (from a share of 0.28 to 0.38). Overhead/profit contribution would increase from $6.16 to $6.53.

Next, we repeat the exercise for Beta, conditional on no change in Alpha price from its status quo of $41. In this case Beta's optimum entails an increase in its price to $41 (which then happens to be at parity with Alpha). Beta's share would decline from 0.72 to 0.65 but its contribution would increase from $13.68 to $14.26. [2]

Next, we consider a unilateral strategic change by Beta – one that both improves its non-price attribute levels (from their current levels to their prospective levels) *and* decreases its price from the original $38 level to $34. Given no retaliation from Alpha, the net effect is to increase Beta's share to 0.868 and its contribution to $13.03.

What should Alpha do if Beta drops to $34 and improves its non-price attributes? Assuming that Alpha's only short-run retaliation is price, the PRIDEM model finds that it should lower price from its starting level of $41 to $34 (at parity with Beta's new price).

Next, we consider a case in which Alpha stays at $41 but Beta really drives down its price (to $28). Moreover, both firms improve their respective non-price attributes to level 2 (prospective levels). The net effect of these actions is that Beta's share markedly increases to 0.933 but its contribution drops substantially (to $8.39).

6.2. Selected segment analysis

At this point we elect to stay with the same non-price parameters as described immediately above. But now we focus on a specific market segmenting variable-type of respondent: nurses, doctors, and pharmacists. PRIDEM shows that the effects on Beta's share differ by segment: 0.892 (nurses), 0.921 (doctors), and 0.982 (pharmacists). Their weighted average is 0.933, as noted above for the total market analysis.

[2] To conserve on space, the analyses to follow are not shown in Figure 2.

```
RUN PRIDEM
INPUT THE NUMBER OF PRODUCTS                                        · Initial parameter inputs
2
INPUT THE NO. OF SEG, PROD./PRICE, AND PRICE ATTRIBUTES
2 6 2
INPUT THE NO. OF LEVELS FOR SEGMENT ATTRIBUTES
3 2
INPUT THE NO. OF LEVELS FOR PRODUCT AND PRICE ATTRIBUTES
2 2 2 2 5 5
INDICATE THE FILE WITH THE SEGMENT WEIGHTS                          · Segment weights file
PRIDEM.WTS
INDICATE THE FILE WITH THE PRICE LEVELS                             · File containing dollar price amounts
PRIDEM.PRI
INPUT THE FILE NAME THAT DESCRIBES THE MODEL                        · Input parameters for Alpha
ALPHA.INP
INPUT 1 FOR TUKEY OR FOR TABLE
2
INDICATE THE NUMBER OF INTERACTION TERMS
4
INPUT THE FILE NAME THAT DESCRIBES THE MODEL                        · Input parameters for Beta
BETA.INP
INPUT 1 FOR TUKEY OR 2 FOR TABLE
2
INDICATE THE NUMBER OF INTERACTION TERMS
4
INPUT 1 IF THE PRICES ARE INCREASING, 0 IF DECREASING
0
INDICATE THE BASE-CASE MARKET SHARES
28 72
INDICATE THE BASE-CASE PROD. NON-PRICE ATT. LEVELS                  · Initial non-price attribute settings
1 1 1 1
INPUT THE BASE-CASE PRICES                                          · Initial price settings
41 38
INPUT THE VARIABLE COSTS PER PRODUCT                                · Initial costs
19 19
INDICATE THE NEW-CASE NON-PRICE ATT. LEVELS                         · Base-case confirmation analysis
1 1 1 1
INPUT THE NEW-CASE PRODUCT PRICES
41 38
INPUT 1 FOR OVERALL, 2 FOR ATTRIBUTE, OR 3 FOR DETAILED ANALYSIS    · Total market analysis for base case
1
THE MARKET SHARES ARE: 0.280 0.720                                  · Shares
THE PROFIT RETURNS ARE: 6.16 13.68                                  · Contributions to overhead/profit
INPUT 1 FOR AN OPTIMAL PRICE ANALYSIS, ELSE 0
1

INPUT THE PRODUCT                                                   · Optimal Alpha price
1                                                                     conditioned on Beta's price
THE OPTIMAL PRICE =36.187
THE MARKET SHARES ARE: 0.38 0.62
THE PROFIT RETURNS ARE: 6.536 11.775
INPUT 1 FOR AN OPTIMAL PRICE ANALYSIS, ELSE 0
1

INPUT THE PRODUCT                                                   Optimal Beta price
2                                                                   conditioned on Alpha's price
THE OPTIMAL PRICE =41.000
THE MARKET SHARES ARE: 0.35 0.65
THE PROFIT RETURNS ARE: 7.743 14.257
INPUT 1 FOR AN OPTIMAL PRICE ANALYSIS, ELSE 0
0
```

Figure 2. Illustrative run of PRIDEM (Main-frame version)

Table 2

Round	Price	
	Alpha	Beta
0	$41	$38
1	$36.19	$38
2	$36.19	$39.83

6.3. *Weighted segment analysis*

To round out the discussion, we also consider a weighted segment analysis for both type of respondent and hospital size. Illustratively, we assign weights of 0.5, 0.4, and 0.1 to nurses, doctors, and pharmacists, respectively. We assign weights of 0.8 and 0.2 to large and small hospitals, respectively.

The net result of this parameter setting is a Beta share of 0.909 and an associated contribution of $8.18. These outputs are each lower than their total market counterparts. [3]

6.4. *Dynamic changes*

Up to this point, our PRIDEM illustration did not explore sequential competitive retaliation. It is, however, a simple matter to use the program in such a way that in Round 1 Alpha initiates action; in Round 2 Beta answers in some fashion, and so on.

By way of illustration, a sequence of actions was implemented, based on starting conditions of $41 (Alpha) and $38 (Beta) with all non-price attributes at their current levels. We assume that Alpha starts out as the price "leader," Beta follows suit, and so on (and each tries to optimize its contribution, conditional on the other's prices). For two such rounds, the results are as can be seen in Table 2.

At the end of two rounds – initiation and response – the prices are $36.19 and 39.83, with shares (contributions) of 0.43 ($7.38) and 0.57 ($11.90) for Alpha and Beta, respectively. Of course, given the ability of Alpha and Beta to collude (if no external competitor were present and if total demand were completely inelastic), they could drive up the prices as much as they liked. (Hence, we do not consider further price changing rounds for this example.)

The idea of an external competitor *can* be incorporated into the PRIDEM model by including a $(P+1)$-st product with fixed prices and non-price attribute levels, and a starting share. Then, if Alpha and Beta tried to drive up their prices the external competitor would garner an increasing share of the market.

7. What have we learned?

How did the study's sponsor react to the PRIDEM model? As we have frequently found in applied studies using the model, the sponsor explored the possibilities for non-price attribute changes. In this example, Beta management added a price guarantee and educational aids. These non-price changes were accompanied by a Beta price *increase* to $41 (at parity with Alpha). As of six months after Beta's changes, Alpha had *not* retaliated with either non-price or price changes. While we are not privy to the financial consequences of Beta's strategy, to the best of our knowledge market share remained relatively stable over the six months' time period in question.

To date, the PRIDEM model has been used on several empirical applications, most frequently drawn from the pharmaceutical industry. The predictions made from the model have been cross-checked, where possible, with time-series analyses of historical price changes. As is well known, analyses of such 'natural experiments' are fraught with difficulty. However, in the cases analyzed, the results have been roughly concordant with those obtained from the model.

The main advantages of the PRIDEM model over that proposed by Mahajan, Green, and Goldberg (1982) are twofold. First, market segment responses can be estimated by means of main effects parameters and interactions with price *and* non-price attribute levels. Second, the present model solves for optimal prices, conditioned on fixed levels for price and non-price attributes of competitive products (using variable cost data estimated by the sponsoring firm's financial department). Moreover, use of the model, as a decision support system, is straightforwardly

[3] By applying weights of 1 and 0, one can find results for each of the six possible segment combinations of respondent profession by hospital size.

implemented by non-technical personnel on either a main-frame of personal computer.

There are several limitations to the model, as currently formulated and operationalized. First, the model deals with aggregated responses, where segment differences are measured by within- and between-set interactions. As Moore (1980) has illustrated, researcher-selected segmenting variables may not adequately capture full individual variation in attribute-level part worths. Second, the model does not make allowance for lack of respondent knowledge about actual prices; in some cases the model could overstate price sensitivity, since full comparative pricing information is shown to the respondents. Third, while the model can handle intra-product line pricing (in terms of within-firm competition), it does not consider joint production/distribution costs.

7.1. Action / reaction sequence

As briefly described earlier, PRIDEM enables the user to examine action/reaction sequences, albeit in a rather simple way that does not consider changes in buyer preferences or other kinds of new information that might be obtained between successive rounds of price changes.

Theoretical work by Hauser and Shugan (1983), Kumar and Sudharshan (1988) and Choi, DeSarbo, and Harker (1990) represent a very interesting topic to pursue in tandem with the measurement aspects of PRIDEM.

To date, management's reaction to PRIDEM's potential for formulating 'dynamic' (action/reaction) strategies has been less than enthusiastic. In our experience managers are much more concerned with the interplay of non-price *and* pricing strategies, with priority given to the former. Bearing in mind that competitive retaliation to non-price actions is typically more difficult and less immediate, this emphasis is understandable.

When managers do engage in action/reaction gaming, their interest usually does not extend to questions of long term equilibria but, rather, is focused on only two to three moves ahead. Again, we do not find these views naive and 'myopic'. Managers typically lack information regarding competitors' costs, motivations and intentions; moveover, they also face questionable assumptions regarding stability in buyers' perceptions and brand preferences over the time period under study.

7.2. Conclusions

These are important caveats and represent opportunities for further research. [4] Hence, we consider the model and its associated decision support system as an interim effort that can (and should) be expanded, consistent with making sure that future versions can be operationalized in terms of accessible buyer preferences and cost data. If we have learned anything from the development of PRIDEM, it is the important fact that useful models must pay due attention to the kinds of measurements and data inputs one hopes to be able to obtain from the environment (e.g., marketplace).

What has made PRIDEM work is the simple fact that conjoint data *can* be obtained in reasonably realistic ways from prospective buyers. Without this measurement linkage (and at the back end, a user-friendly computer system), PRIDEM could have easily joined the ranks of a large array of technically attractive models with few (or no) users.

Appendix

In this section we describe, in further detail, the spline fitting procedure that enabled us to interpolate between the discrete price points utilized in the experimental design.

A.1. Fitting one-dimensional splines

Let g be a function of one variable. Assume that we know the value of g at $\xi_0 \leq \cdots \leq \xi_n$ (i.e., at $n+1$ knots). We want to interpolate to find $g(x)$ smoothly; $\forall x \in [\xi_0, \xi_n]$. We approximate $g(x)$ by a p-dimensional polynomial in each interval $[\xi_{i-1}, \xi_i]$, $i = 1, \ldots, n$. Note that the

[4] For other illustrations of recent developments in pricing research, see DeSarbo et al. (1987), Nagle (1984), Rao (1984), and Robinson and Lakhani (1975).

meaning of the variables here (e.g., p below) is different from that used in the main text. That is,

$$g(x) = \sum_{j=0}^{p} \alpha_{ij} x^j \quad \text{for } \xi_{i-1} \le x \le \xi_i.$$

Let $g^{(k)}$ denote the k-th derivative of x. We know $g(\xi_{i-1})$ and $g(\xi_i)$; for smoothness we assume that $\lim_{x \uparrow \xi_{i-1}} g^{(k)}(x) = \lim_{x \downarrow \xi_{i-1}} g^{(k)}(x)$ for $k = 1, \ldots, p-1$. This gives us $p+1$ linear equations in $p+1$ unknowns and hence $\alpha_{i0}, \ldots, \alpha_{ip}$ are determined. Specifically, let $v_1 = g(\xi_{i-1})$, $v_2 = g(\xi_i)$ and $t_k = \lim_{x \uparrow \xi_{i-1}} g^{(k)}(x)$, $k = 1, \ldots, p-1$. Let $\boldsymbol{\alpha}_i = (\alpha_{i0}, \ldots, \alpha_{ip})$ and

$$X = \begin{bmatrix} 1 & \xi_{i-1} & \cdots & \xi_{i-1}^p \\ 1 & \xi_i & \cdots & \xi_i^p \\ 0 & 1 & \cdots & p\xi_{i-1}^{p-1} \\ & & & \vdots \\ 0 & 0 & \cdots & p!\xi_{i-1} \end{bmatrix}.$$

Then,

$$\boldsymbol{\alpha} X = \begin{bmatrix} v_1 \\ v_2 \\ t_1 \\ \vdots \\ t_{p-1} \end{bmatrix},$$

from which

$$\boldsymbol{\alpha} = X^{-1} \begin{bmatrix} v_1 \\ v_2 \\ t_1 \\ \vdots \\ t_{p-1} \end{bmatrix}.$$

All we need to specify exogenously is $g^{(1)}(\xi_0), \ldots, g^{(p-1)}(\xi_0)$.

Linear interpolation is a special case of the above. Solving for $(\alpha_{i0}, \alpha_{i1})$ yields

$$\alpha_{i1} = \frac{g(\xi_i) - g(\xi_{i-1})}{\xi_i - \xi_{i-1}}$$

and

$$\alpha_{i0} = g(\xi_{i-1}) - \xi_{i-1}\alpha_{i1}.$$

A.2. Fitting two-dimensional splines

Let g be a function of two variables. Assume that we know the value of g at the lattice of points (ξ_i, ξ_j'), $i = 1, \ldots, m$, $j = 1, \ldots, n$. We want to interpolate to find $g(x, y)$ smoothly for all x and y, $\xi_0 \le x \le \xi_m$ and $\xi_0' \le y \le \xi_n'$. We approximate $g(x, y)$ by a polynomial in each rectangle $\xi_{i-1} \le x \le \xi_i$, $\xi_{j-1}' \le y \le \xi_j'$. That is,

$$g(x, y) = \sum_{k=0}^{p} \sum_{l=0}^{p} \alpha_{ijkl} x^k y^l$$

$$\text{for } \xi_{i-1} \le x \le \xi_i \text{ and } \xi_{j-1}' \le y \le \xi_j'.$$

In a manner similar to the one-dimensional case, smoothness conditions and $t_{00} \equiv g(\xi_{i-1}, \xi_{j-1}')$, $t_{01} \equiv g(\xi_{i-1}, \xi_j')$, $t_{10} \equiv g(\xi_i, \xi_{j-1}')$, and $t_{11} \equiv g(\xi_i, \xi_j')$ determine the α_{ijkl}. In particular, let $p = 1$. Then $g(x, y) = \alpha_{ij00} + \alpha_{ij10}x + \alpha_{ij01}y + \alpha_{ij11}xy$. We then have four linear equations in four unknowns

$$t_{00} = \alpha_{ij00} + \alpha_{ij10}\xi_{i-1} + \alpha_{ij01}\xi_{j-1}' + \alpha_{ij11}\xi_{i-1}\xi_{j-1}',$$

$$t_{01} = \alpha_{ij00} + \alpha_{ij10}\xi_{i-1} + \alpha_{ij01}\xi_j' + \alpha_{ij11}\xi_{i-1}\xi_j',$$

$$t_{10} = \alpha_{ij00} + \alpha_{ij10}\xi_i + \alpha_{ij01}\xi_{j-1}' + \alpha_{ij11}\xi_i\xi_{j-1}',$$

and

$$t_{11} = \alpha_{ij00} + \alpha_{ij10}\xi_i + \alpha_{ij01}\xi_j' + \alpha_{ij11}\xi_i\xi_j'.$$

These four equations have the solution:

$$\alpha_{ij11} = \frac{t_{11} - t_{10} - t_{01} + t_{00}}{\xi_i\xi_j' - \xi_i\xi_{j-1}' - \xi_{i-1}\xi_j' + \xi_{i-1}\xi_{j-1}'},$$

$$\alpha_{ij10} = \frac{t_{10} - t_{00} - \alpha_{ij11}\xi_{j-1}'(\xi_i - \xi_{i-1})}{\xi_i - \xi_{i-1}},$$

$$\alpha_{ij01} = \frac{t_{01} - t_{00} - \alpha_{ij11}\xi_{i-1}(\xi_j' - \xi_{j-1}')}{\xi_j' - \xi_{j-1}'},$$

and

$$\alpha_{ij00} = t_{00} - \alpha_{ij10}\xi_{i-1} - \alpha_{ij01}\xi_{j-1}' - \alpha_{ij11}\xi_{i-1}\xi_{j-1}'.$$

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APPENDIX B

MASTER EXPERIMENTAL DESIGN CARDS Nos. 1 – 140

ARRANGED IN 20 BLOCKS OF 7 CARDS EACH

1	2	3	1	1	1	4	3	3	3	5	2	2	1
2	1	3	1	1	1	1	1	6	1	7	4	3	1
4	4	2	4	2	3	4	1	2	4	4	5	4	1
1	2	2	2	3	3	2	2	4	5	7	6	7	1
3	1	1	2	2	4	3	4	5	6	6	3	6	1
2	3	4	3	4	2	3	3	1	7	3	1	5	1
3	3	1	4	3	2	1	2	7	2	2	3	1	1
1	1	1	4	2	2	3	2	6	2	1	4	4	2
4	4	2	3	1	4	4	3	4	6	7	3	7	2
2	3	3	2	3	1	4	3	7	4	6	2	4	2
3	4	4	2	1	1	1	1	2	5	2	6	2	2
2	1	2	4	3	3	2	2	3	3	5	1	5	2
4	2	4	1	4	2	2	4	1	1	3	5	3	2
3	2	3	3	2	3	1	1	5	7	1	4	1	2
1	3	1	2	1	1	1	3	4	5	3	5	5	3
4	2	3	4	3	4	4	4	3	6	1	1	4	3
3	4	2	1	4	1	1	4	1	1	6	7	7	3
1	3	3	2	3	2	3	2	6	3	4	3	1	3
2	4	4	3	4	3	3	3	7	2	1	6	2	3
3	1	4	1	2	4	2	1	2	7	5	4	7	3
1	2	1	3	1	3	4	1	5	4	7	2	3	3
3	4	3	3	1	1	2	4	6	4	3	1	1	4
2	2	4	3	3	1	3	4	4	1	2	2	6	4
3	1	1	4	3	3	4	3	7	5	1	3	3	4
1	1	3	2	2	2	1	3	3	6	4	6	2	4
2	4	2	1	4	3	4	2	5	7	5	5	5	4
4	2	1	1	2	2	3	1	4	3	2	7	6	4
1	3	2	2	1	4	4	1	1	2	6	4	4	4
4	1	2	2	4	1	1	4	6	5	1	3	4	5
1	3	3	1	3	1	3	4	3	2	7	5	5	5
1	2	2	1	2	4	3	3	5	1	3	1	7	5
4	3	4	3	2	3	1	2	2	4	2	4	6	5
3	3	1	3	4	4	4	2	7	3	5	7	1	5
3	4	3	4	1	3	2	1	4	5	4	6	4	5
2	1	1	3	4	2	4	1	3	4	3	5	6	6
3	2	4	2	1	3	3	4	5	6	5	1	4	6
1	3	4	1	4	1	1	3	2	3	1	3	3	6
4	2	2	3	1	2	1	3	1	5	4	6	1	6
2	1	2	2	3	4	2	3	6	4	2	7	5	6
1	3	1	4	2	4	2	4	4	7	7	2	2	6
4	4	3	4	2	3	3	2	7	1	6	4	1	6
1	1	4	4	4	4	2	4	7	6	4	5	6	7
4	4	1	4	4	2	1	1	3	5	2	1	7	7
3	1	2	3	1	1	4	2	4	6	3	4	1	7
2	2	1	1	2	3	1	3	2	2	5	2	4	7
3	3	3	3	2	2	4	4	6	1	6	7	5	7
4	4	2	1	3	1	3	2	1	4	1	6	3	7
2	4	4	2	3	4	2	1	1	3	7	3	2	7
4	1	4	4	1	1	1	2	5	7	4	5	1	8
1	4	3	3	2	4	1	4	1	3	2	2	5	8
3	3	2	3	4	3	2	3	4	2	6	1	3	8
2	2	1	1	4	3	3	2	3	4	1	6	7	8
1	4	1	2	3	2	2	1	7	1	5	1	3	8
2	2	2	2	3	2	4	4	6	5	7	4	6	8
4	3	3	4	1	4	4	1	2	6	3	7	2	8
3	3	2	3	3	4	1	3	6	7	5	6	6	9
1	1	3	4	3	3	1	1	5	1	6	2	7	9
2	2	2	4	4	1	3	3	2	6	4	7	3	9
2	4	1	2	2	2	2	4	4	3	1	5	4	9
3	2	3	1	4	4	3	1	1	5	5	4	5	9
4	4	4	1	1	3	4	4	3	2	7	3	1	9
4	1	1	2	2	1	2	2	7	2	3	1	2	9
3	1	2	3	3	2	1	4	5	2	4	2	2	10
1	3	2	1	4	3	2	1	6	6	2	5	1	10
4	2	1	2	4	3	4	3	1	7	4	1	6	10
4	3	3	2	2	2	2	3	7	4	7	4	7	10
2	1	1	4	1	4	3	4	2	3	6	6	5	10
1	2	4	4	1	1	1	2	4	4	1	7	2	10
4	2	4	3	1	2	2	2	2	6	5	2	5	11
1	4	3	4	3	3	2	3	1	2	3	7	6	11
2	3	1	1	1	3	3	3	6	1	4	3	2	11
3	2	4	4	2	1	4	2	6	3	6	5	7	11
2	4	2	1	2	4	1	1	4	7	6	6	1	11
1	1	2	3	4	1	1	1	7	3	7	1	4	11
4	3	1	2	4	4	3	4	5	5	2	4	3	11
3	1	1	1	1	2	2	2	1	6	4	2	7	12
2	2	4	2	2	1	4	1	6	2	4	1	7	12
4	3	1	2	3	3	3	1	3	1	3	7	2	12
1	4	3	3	3	1	4	4	2	7	5	5	6	12
3	2	3	1	1	2	1	4	7	4	6	3	5	12
2	3	2	3	2	4	2	2	3	5	1	2	3	12
4	4	3	4	4	4	4	3	5	3	2	4	2	12
3	2	2	2	2	1	3	1	7	6	2	5	2	13
1	1	4	4	2	3	4	4	1	5	5	7	1	13
4	3	4	1	3	1	2	1	5	2	6	6	6	13
3	3	2	1	2	4	1	4	3	4	4	1	3	13
4	4	1	4	1	4	3	3	6	7	7	2	5	13
1	1	1	3	4	2	4	3	2	1	1	6	7	13
2	2	3	3	1	2	2	2	5	3	3	3	4	13
2	3	3	4	2	3	1	2	1	6	7	1	6	14
1	1	4	1	4	4	2	2	6	5	6	2	2	14
1	4	2	3	1	2	3	1	5	2	2	7	3	14
2	3	4	4	4	3	4	4	4	2	3	3	7	14
4	3	2	2	1	2	3	4	7	7	5	6	4	14
3	2	3	2	3	4	2	3	2	1	1	5	1	14
3	1	1	1	3	1	4	3	4	4	4	4	5	14
3	4	3	2	4	3	3	4	2	7	3	2	7	15
1	1	4	2	1	4	3	3	4	4	2	1	1	15
2	4	3	1	3	4	4	2	7	5	4	7	3	15
3	3	1	4	4	1	4	2	5	3	7	6	4	15
1	2	2	3	2	1	2	1	3	7	4	3	6	15
2	3	2	4	1	2	1	4	1	1	5	4	2	15

Appendix B (con't)

MASTER EXPERIMENTAL DESIGN CARDS Nos. 1 – 140,

ARRANGED IN 20 BLOCKS OF 7 CARDS EACH

4	1	3	1	3	1	2	3	1	7	2	3	4	16
2	4	1	3	2	1	4	4	6	6	5	6	3	16
3	4	2	2	1	4	4	2	5	1	1	2	6	16
4	2	2	4	4	2	2	3	4	4	6	2	1	16
3	2	4	2	4	4	1	1	3	2	7	7	5	16
1	3	4	3	3	3	3	4	7	3	4	4	7	16
2	1	3	1	1	2	3	2	2	5	7	1	6	16
1	2	3	4	4	2	1	2	6	7	3	6	3	17
1	4	1	2	4	1	2	4	2	2	4	4	5	17
3	3	4	3	1	3	2	3	3	1	2	5	4	17
4	2	1	3	3	4	3	2	1	5	6	5	2	17
4	1	2	1	1	3	2	4	7	3	1	7	6	17
2	1	4	4	3	4	3	1	4	4	5	3	7	17
2	4	1	1	2	2	1	3	5	6	7	7	1	17
2	2	3	1	1	4	1	2	7	2	2	5	7	18
1	3	4	1	2	2	4	1	5	5	1	1	5	18
4	1	3	3	4	1	3	2	4	1	7	7	4	18
4	4	1	3	3	3	1	4	2	6	6	1	2	18
2	2	1	4	3	1	2	4	3	7	2	4	1	18
3	1	4	2	2	3	4	3	1	3	3	6	3	18
3	4	2	4	4	2	3	1	6	4	5	3	6	18
3	4	4	1	3	2	4	2	4	7	2	1	2	19
1	4	1	2	1	3	1	2	3	3	6	4	6	19
4	3	3	3	2	1	2	3	5	5	5	3	7	19
2	3	3	2	4	1	3	1	1	6	1	2	1	19
1	2	1	1	3	4	1	4	6	4	3	7	4	19
3	1	2	4	2	2	3	3	2	2	7	5	3	19
4	2	4	4	4	4	2	1	7	1	4	6	5	19
2	4	4	4	2	1	1	3	7	5	3	2	6	20
4	1	3	2	4	4	1	2	4	2	5	5	3	20
3	3	1	4	1	1	2	1	1	7	1	7	7	20
1	2	2	2	2	3	4	2	2	1	2	3	5	20
4	3	2	1	3	2	4	1	2	3	3	2	1	20
2	1	3	3	4	3	2	4	5	4	7	6	2	20

Appendix C

ILLLUSTRATIVE STIMULI CARDS

C001

5-7

(1) Plastic Teeth BRAND/LINE	(2) Anterior Card (1 x 6) PRICE IN $	(3) Available From: LOCAL DEALER	MAIL-ORDER DEALER	MANUFACTURER DIRECTLY	(4) Your Response: SHARE OF PURCHASES (PERCENT)	
Dentsply BIOFORM IPN	19.44	Yes	No	Yes		8-10
Dentsply BIOBLEND IPN	23.71	Yes	No	Yes		11-13
Dentsply CLASSIC	3.90	Yes	No	Yes		14-16
Dentsply PORTRAIT IPN	26.28	Yes	No	Yes		17-19
Dentsply TRUBLEND SLM	22.22	Yes	No	Yes		20-22
Ivoclar SR VIVODENT PE	20.04	Yes	No	Yes		23-25
Justi BLEND	12.84	Yes	Yes	Yes		26-28
Kenson RESIN	3.75	Yes	Yes	Yes		29-31
Myerson DURABLEND SPECIAL RESIN	15.96	No	Yes	Yes		32-34
Universal VERILUX	26.84	Yes	Yes	No		35-37
Vita VITAPAN	29.01	Yes	Yes	No		38-40
				Total =	100 points	

C002

5-7

(1) Plastic Teeth BRAND/LINE	(2) Anterior Card (1 x 6) PRICE IN $	(3) Available From			(4) Your Response: SHARE OF PURCHASES (PERCENT)	
		LOCAL DEALER	MAIL-ORDER DEALER	MANUFACTURER DIRECTLY		
Dentsply BIOFORM IPN	21.76	No	Yes	No		8-10
Dentsply BIOBLEND IPN	21.07	No	Yes	No		11-13
Dentsply CLASSIC	3.90	No	Yes	No		14-16
Dentsply PORTRAIT IPN	26.28	No	Yes	No		17-19
Dentsply TRUBLEND SLM	22.22	No	Yes	No		20-22
Ivoclar SR VIVODENT PE	20.04	Yes	Yes	Yes		23-25
Justi BLEND	12.84	Yes	Yes	Yes		26-28
Kenson RESIN	3.75	Yes	Yes	Yes		29-31
Myerson DURABLEND SPECIAL RESIN	15.96	No	No	Yes		32-34
Universal VERILUX	19.52	Yes	No	No		35-37
Vita VITAPAN	23.21	Yes	No	Yes		38-40
				Total =	100 points	

C003

5-7

(1) Plastic Teeth BRAND/LINE	(2) Anterior Card (1 x 6) PRICE IN $	(3) Available From			(4) Your Response: SHARE OF PURCHASES (PERCENT)	
		LOCAL DEALER	MAIL-ORDER DEALER	MANUFACTURER DIRECTLY		
Dentsply BIOFORM IPN	26.60	Yes	Yes	No		8-10
Dentsply BIOBLEND IPN	28.97	Yes	Yes	No		11-13
Dentsply CLASSIC	3.90	Yes	Yes	No		14-16
Dentsply PORTRAIT IPN	23.65	Yes	Yes	No		17-19
Dentsply TRUBLEND SLM	30.56	Yes	Yes	No		20-22
Ivoclar SR VIVODENT PE	22.55	Yes	No	No		23-25
Justi BLEND	12.84 f	Yes	Yes	Yes		26-28
Kenson RESIN	3.75 f	Yes	Yes	Yes		29-31
Myerson DURABLEND SPECIAL RESIN	19.95	Yes	No	No		32-34
Universal VERILUX	26.84	No	Yes	Yes		35-37
Vita VITAPAN	23.21	Yes	No	No		38-40
				Total =	100 points	

C004

5-7

(1) Plastic Teeth BRAND/LINE	(2) Anterior Card (1 x 6) PRICE IN $	(3) Available From			(4) Your Response: SHARE OF PURCHASES (PERCENT)	
		LOCAL DEALER	MAIL-ORDER DEALER	MANUFACTURER DIRECTLY		
Dentsply BIOFORM IPN	19.44	Yes	No	No		8-10
Dentsply BIOBLEND IPN	23.71	Yes	No	No		11-13
Dentsply CLASSIC	3.90	Yes	No	No		14-16
Dentsply PORTRAIT IPN	23.65	Yes	No	No		17-19
Dentsply TRUBLEND SLM	25.00	Yes	No	No		20-22
Ivoclar SR VIVODENT PE	25.05	No	Yes	Yes		23-25
Justi BLEND	12.84	Yes	Yes	Yes		26-28
Kenson RESIN	3.75 f	Yes	Yes	Yes		29-31
Myerson DURABLEND SPECIAL RESIN	19.95 f	No	No	Yes		32-34
Universal VERILUX	21.96	No	Yes	No		35-37
Vita VITAPAN	26.11	No	No	Yes		38-40
				Total =	100 points	

C005

5-7

(1) Plastic Teeth BRAND/LINE	(2) Anterior Card (1 x 6) PRICE IN $	(3) Available From			(4) Your Response: SHARE OF PURCHASES (PERCENT)	
		LOCAL DEALER	MAIL-ORDER DEALER	MANUFACTURER DIRECTLY		
Dentsply BIOFORM IPN	24.18	No	Yes	Yes		8-10
Dentsply BIOBLEND IPN	21.07	No	Yes	Yes		11-13
Dentsply CLASSIC	3.90	No	Yes	Yes		14-16
Dentsply PORTRAIT IPN	21.02	No	Yes	Yes		17-19
Dentsply TRUBLEND SLM	25.00	No	Yes	Yes		20-22
Ivoclar SR VIVODENT PE	22.55	No	Yes	No		23-25
Justi BLEND	12.84	Yes	Yes	Yes		26-28
Kenson RESIN	3.75	Yes	Yes	Yes		29-31
Myerson DURABLEND SPECIAL RESIN	21.95	No	Yes	No		32-34
Universal VERILUX	24.40	Yes	No	Yes		35-37
Vita VITAPAN	31.91	No	Yes	No		38-40
				Total =	100 points	

C006

5-7

(1) Plastic Teeth BRAND/LINE	(2) Anterior Card (1 x 6) PRICE IN $	(3) Available From			(4) Your Response: SHARE OF PURCHASES (PERCENT)	
		LOCAL DEALER	MAIL-ORDER DEALER	MANUFACTURER DIRECTLY		
Dentsply BIOFORM IPN	21.76	Yes	Yes	Yes		8-10
Dentsply BIOBLEND IPN	26.34	Yes	Yes	Yes		11-13
Dentsply CLASSIC	3.90	Yes	Yes	Yes		14-16
Dentsply PORTRAIT IPN	28.91	Yes	Yes	Yes		17-19
Dentsply TRUBLEND SLM	27.78	Yes	Yes	Yes		20-22
Ivoclar SR VIVODENT PE	27.56	No	No	Yes		23-25
Justi BLEND	12.84	Yes	Yes	Yes		26-28
Kenson RESIN	3.75	Yes	Yes	Yes		29-31
Myerson DURABLEND SPECIAL RESIN	17.96	Yes	No	Yes		32-34
Universal VERILUX	24.40	Yes	Yes	Yes		35-37
Vita VITAPAN	29.01	No	Yes	Yes		38-40
				Total =	100 points	

C007

5-7

(1) Plastic Teeth BRAND/LINE	(2) Anterior Card (1 x 6) PRICE IN $	(3) Available From			(4) Your Response: SHARE OF PURCHASES (PERCENT)	
		LOCAL DEALER	MAIL-ORDER DEALER	MANUFACTURER DIRECTLY		
Dentsply BIOFORM IPN	24.18	No	No	Yes		8-10
Dentsply BIOBLEND IPN	26.34	No	No	Yes		11-13
Dentsply CLASSIC	3.90	No	No	Yes		14-16
Dentsply PORTRAIT IPN	21.02	No	No	Yes		17-19
Dentsply TRUBLEND SLM	30.56	No	No	Yes		20-22
Ivoclar SR VIVODENT PE	25.05	Yes	Yes	No		23-25
Justi BLEND	12.84	Yes	Yes	Yes		26-28
Kenson RESIN	3.75	Yes	Yes	Yes		29-31
Myerson DURABLEND SPECIAL RESIN	17.96	Yes	Yes	No		32-34
Universal VERILUX	19.52	Yes	No	Yes		35-37
Vita VITAPAN	26.11	Yes	Yes	Yes		38-40
				Total =	100 points	